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# Evaluation of Correlations Between Meteorological Measurements and Observations of Lightning Activity Using Artificial Neural Systems

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**This report shows the feasibility of using artificial neural systems (ANS) for making predictions of cloud to ground lightning strikes. ANS designs offer some potentially useful features. ANS predictors can be incrementally trained for new levels of performance without starting programming from 'scratch' each time the predictor is upgraded. Incremental training could proceed in the field reducing costs and delays of modifications while improving predictor accuracy by tailoring it to site conditions (i.e. topography, etc). Trained ANS provides a ready-made formula for constructing fast parallel, distributed processors. The features built up within the ANS might be analyzed for clues to the physical processes underlying the partially understood phenomenon of lightning. Comparisons are made of the performance of an ANS predictor with the state-of-the-art lightning prediction using a wind convergence based criterion described by Watson et al, 1987. The results show that ANS lightning prediction has achieved performance levels comparable to the previous state-of-the-art. It is expected that ANS predictive power will increase when many inputs (e.g. electric field, wind divergence, temperature, humidity, satellite cloud altitudes and radar returns) are simultaneously included in the input and when many days' data are used in training.**

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# Executive Summary

Lightning strikes have caused damage reaching hundreds of millions of dollars during major unmanned launches, and lightning could lead to loss of life on shuttle launches. Reliable predictions of lightning strikes would be invaluable. This report shows the feasibility of using artificial neural systems (ANS) for making predictions of cloud to ground lighting strikes. ANS provides a tool for cost-effectively building lightning prediction machines with advantages over standard programming.

ANS designs offer some potentially useful features. First, an ANS predictor can be incrementally trained for new levels of performance without starting programming from 'scratch' each time the predictor is upgraded. Second, incremental training could proceed in the field reducing costs and delays of modifications while improving predictor accuracy by tailoring it to site conditions (i.e. topography, etc.). Third, a trained ANS provides a ready-made formula for constructing fast parallel, distributed processors. Fourth, the features built up within the ANS might be analyzed for clues to the physical processes underlying the partially understood phenomenon of lightning.

Comparisons are made of the performance of an ANS predictor with the state of the art lightning prediction using a wind convergence based criterion described by Watson et al. 1987. Using the total area divergence of the winds at the Kennedy Space Center, one predicts lightning when this quantity is less than a certain negative threshold. An ANS was trained to wind inputs and known lightning events. Both the ANS and wind total area divergence methods were applied for similar conditions. The results show that ANS lightning prediction has achieved performance levels comparable to the previous state of the art as shown below.

Comparison of this Study's Results with those of Watson et al. (1987)

| Type of Measure | This Study | Watson, et al. (1987) |
|---|---|---|
| Probability of Detection | 0.41 | 0.47 |
| False Alarm Ratio | 0.57 | 0.56 |
| Critical Skill Index | 0.26 | 0.29 |

Given the complexity of lightning strikes, the current results should be understood as indicative of a promising initiative and cannot be considered definitive. Therefore, recommendations for future work are made. The results in the Table were obtained using one day's raw wind speed and direction data as training input to the ANS. A different day's wind data were used for testing ANS predictions. Synthesis of different data types is one of the possibilities of employing ANS. It is expected that ANS predictive power will increase when many inputs (e.g. electric field, wind divergence, temperature, humidity, satellite cloud altitudes, and radar returns) are simultaneously included in the input. Predictive power should also improve when many days' data are used in training. A program of recommended research and development tasks is given for advancing the state of the art of lightning predictors which use ANS.

# Preface

The concept of using artificial neural systems (ANS) for predicting lightning strokes was developed in the summer of 1987 by the staff of KTAADN, INC., including Dr. James Stark Draper and Dr. Donald S. Frankel in planning meetings with Dr. Robert McClatchey, Dr. Arnold Barnes, and Dr. James Metcalf of the Geophysics Laboratory (GL). Subsequently, under sponsorship by GL under Air Force Contract No. F19628-89-C-0012 the pilot study reported here was initiated.

The authors wish to acknowledge the invaluable advice and support of Dr. Arnold Barnes (GL/LYA) and Dr. James Metcalf (GL/LYR). Dr. Ralph Markson of Airborne Research Associates, Inc., Weston, Massachusetts, served as lead consultant for this project. Drs. Irv Watson and Ron Holle (NOAA/ERL) described their research and provided critical lightning strike histories for this work. Mr. Billy Boyd, Mr. Hal Herring and other individuals of CSR/Weather, NASA and Air Force personnel at the Kennedy Space Center provided the meteorological data needed in this study. The extensive and professional help of Ms. Barbara J. Levine in preparing contract and report materials is gratefully acknowledged. Acknowledgement is given to Mr. Randall W. Bergmann, manager of the Defense Technical Information Center at Hanscom Air Force Base, for his ready and expert help with finding important references.

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# 1. Lightning & Missile Launches: A Pilot Study

A lightning strike to a rocket, either on a launch pad or during boost through the troposphere, could result in a devastating loss. Danger to rocket launches from lightning first came into prominence when the Apollo 12 Saturn V vehicle was struck twice, at altitudes of 2 and at 4.2 km (Brook et al., 1970). The second stroke initiated a rapid tumbling of the inertial navigation subsystem which would have terminated the mission but for the lucky fact that this subsystem was not in use at that time. The loss of a communications satellite atop an Atlas Centaur rocket represented a loss of some $160 million (Wilford, 1987; Doherty , 1987). There is also danger to fueling crews and other ground assets. This situation has led the USAF, NASA and NOAA to consider various means for reducing the lightning threat.

## 1.1. Coping with Lightning

Both structural and electrical damage may occur due to lightning striking a rocket just before or during launch. In the first type, the rocket body and its ionized gas trail (the rocket exhaust) acts as a 'stationary discharge channel' in which excessive currents burn out circuits and structural pieces. In the second type, rapidly changing magnetic fields due to nearby lightning strokes causes EMP (electromagnetic pulse) damage to circuits. Either type of damage can be reduced by several approaches.

Efforts to cope with the potential of lightning damage appear to fall into one of several approaches:

(1) **Prevention of Damage when Struck** - Prevention by better design, documented by Gabrielson (1988), can be attained using lightning rods and otherwise heavily shielded installations. In 1982 the shuttle launch tower was protected from a 29 kA stroke which was grounded by a lightning rod protection system (Anon, 1983).

(2) **Avoidance of Being Struck** - Avoidance methods may be classed in either flexible or non-flexible approaches. Historical averages of local stroke activity can be used to show which locales ought to be avoided. Historical averages are of no help when dealing with an existing facility such as The Kennedy Space Center (KSC).

'Avoidance' could be aided by time-dependent predictions which KSC operations personnel might use in positioning the rocket and scheduling launches. One time-dependent approach is the adherence to an inflexible policy of waiting for 'perfect' conditions (clear sky, low humidity, etc.). Limiting launches to 'perfect' conditions unnecessarily sacrifices valuable launch windows, such as those controlled by astronomical events.

A more flexible approach is preferred. One can imagine the value of high credibility predictions (e.g. >70% chance of a strike at area [i,j] in 1 to 2 hours) which vary with time (i.e. are 'flexible') as environmental conditions vary. This type of approach, were its credibility proven, would provide KSC operations with a rational basis for making decisions as to how to avoid damage.

Mr. William Jafferis, a NASA program manager, emphasizes the need for lightning forecasting over the coming 1/2 hr to 3 hr interval at KSC (Fincher, 1988). In sum, a method for providing time-dependent stroke predictions is clearly of interest.

## 1.2. Approach of the Pilot Study

The investigation of a time dependent prediction method using artificial neural systems (ANS) for Kennedy Space Center (KSC) is the subject of this pilot study. KSC is a particularly challenging launch locale for protection from lightning sir :e it is one of the most active lightning strike areas in the United States (Doherty, 1987). The attainment of a prediction capability that is comparable to the current state of the art using ANS is the goal of this study. Success in this effort would encourage further development of ANS techniques for building lightning predictors. Two considerations recommend the use of ANS (often termed 'neural networks'). The first is that one can train a useful neural network even though our understanding of lightning physics remains incomplete. The second is the suitability of ANS to the prediction of future events. These two topics are dealt with in the next two paragraphs.

The extensive data sets at KSC and the partial knowledge of lightning events makes ANS a suitable tool for building a lightning predictor. This situation is well described by Caudill (1989): "Neural Networks are extremely valuable for the situation where we don't know exactly what features are important , but we do have an idea of some likely ones. When this situation occurs, we can shorten the training needed by the network (sometimes substantially) by setting up a preset bias toward the features we think are important. This method is often performed when the network designer has some domain knowledge of the problem being attacked, and it generally results in better network designs and much faster training. And in some problems the network designer knows nothing at all about the problem, so the network has to build the feature detectors from scratch, or rather from a random set of weights. Such a network could work very well, assuming an appropriate architecture for the problem is at hand, although it may take longer to train than if the designer gives it a head start." Therefore, as some understanding of the current knowledge of lightning is valuable in building ANS, we discuss the phenomenology of lightning in section 2.0.

Weather is often viewed as a chaotic time series with underlying 'attractors' or a deterministic 'map' conveying the immanent meteorological physics. We have, in the previous paragraph, conveyed the notion that, with some understanding of the knowledge domain under discussion, a good first cut neural network architecture (nodes and link topology) can be achieved. Lapedes and Farber (1987) have shown the value of ANS used for predicting the future behavior of complicated systems which appear to behave 'chaotically'. Examples of this type of 'deterministic chaos' are turbulence in fluids, chemical reactions, plasma physics and weather. Lapedes and Farber conclude that nonlinear ANS perform well in this application as they build very good approximations of the underlying maps. Performing well means, for Lapedes and Farber, that the ANS provided 'excellent prediction of complicated, "random," time series'.

A final, compelling consideration for choosing ANS in this pilot study is the evaluation of the possibility of making a weather data analysis tool which runs on 'off-the-

shelf hardware (a Macintosh IIx)[1]. With a suitable software interface, the design of which has been guided by meteorologists, a competent meteorologist (not a computer scientist) would be able to use this data analysis tool in his/her own office to carry out research and build predictors using his or her own data.

This study had as its primary goal the examination of the feasibility of training ANS for the prediction of lightning strikes at KSC. Secondarily, some features of a prototype tool for the use of meteorologists who wish to analyze large masses of data were investigated. Last, recommendations for subsequent effort were prepared.

## 2. Prediction: State of the Art

The state of the art of predicting lightning strokes is based upon knowledge of the physics of charged clouds and familiarity with meteorological data from the locale under investigation. Lightning physics reviews are available (Williams, 1988; Uman, 1988, 1989). Available prediction studies are described which will be used to benchmark the results of this study.

### 2.1. Physics of Lightning

Cloud to ground lightning strokes from convection cells that appear as thunderclouds (cumulonimbus) are considered here (see Figure 2.1). Snowstorms, sandstorms, volcanic eruption clouds, and even clear air conditions have produced discharges (Gabrielson, 1988); these types of lightning are not discussed.

Vertical winds leading to the collision of particles with a consequent charge separation are the ultimate source of electrified clouds. There is no complete theory of lightning discharges. Many physical aspects of lightning are not well understood and are controversial (Anon , 1989b). Extensive anecdotal information and quantitative collections of related meteorological data are available. An understanding of the general behavior of lightning is invaluable in designing ANS for predictors of lightning strokes.

A number of relevant observations about the physics of lightning will be valuable for this study. Thunderclouds are usually isolated 'cells' or lines of cells associated with advancing cold fronts (Uman, 1986). The isolated cell, shown in Figure 2.1, follows a typical life cycle: cumulus, mature, and dissipating. As sun-driven thermals rise, humid air cools at a lapse rate of 3.3 F per 1,000 feet of altitude while surrounding dry air cools at 5.5 F per 1,000 feet of altitude. The lower cooling rate of humid air results from heat released as water vapor condenses. Under these unstable conditions the humid air continues to rise until the atmospheric temperature profile reverses at 15 to 20 km and the cloud top flattens out in its characteristic 'anvil profile'. The upward motion is termed vertical convection and the cell is sometimes called a 'convection center.' While central to the storm development, vertical air flow is not measured by Doppler radars that follow the horizontal flow or 'convergence' winds (see Figure 2.1). Convergence has been emerging as a key parameter in lightning forecasting.(Lopez et al., 1986a and 1986b).

During formation, the surface (sometimes termed 'low level') winds 'converge' at the bottom of the cloud (see Figure 2.1) and a cumulus cloud rapidly rises to mature as a cumulonimbus over a period of an hour. At maturity, precipitation and lightning

[1] Macintosh is a registered trademark of Apple Computer, Inc.

discharges are typically most plentiful (Watson et al., 1987, 1989a and b). In its final stages the cloud collapses, strong surface wind divergence appears and the cell disperses in about an hour. Advancing cold fronts will bring longer precipitation periods because a line of cells may pass overhead. It is expected that a lightning prediction method will benefit from distinguishing between cells (which evolve overhead) and cold fronts which rapidly pass through one's area. These two regimes are for calm weather (in which stationary cells develop in one area) and a moving weather (front) 'flow regime'. At KSC the moving flow regime further subdivides into direction (NE, SE, SW, and NW) with markedly differing lightning flash results (Holle et al., 1988).

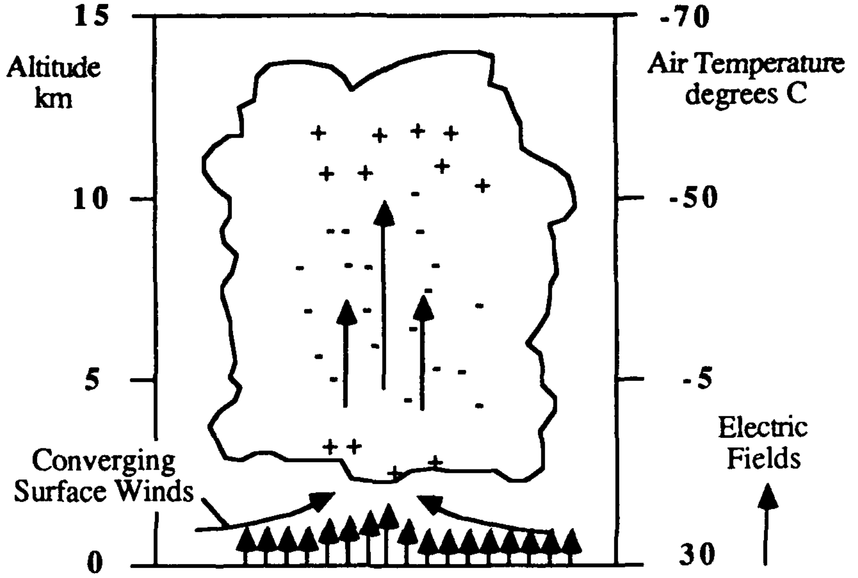


Figure 2.1 Distribution of Thundercloud Charges (Milan 1963) with an Overlay of the Converging Surface Winds which Feed the Upward Flow.

Thunderclouds contain vertically moving air columns in which rising and falling particles collide leading to a separation of charges (Williams, 1988). The separated charges build up in restricted regions, shown in Figure 2.1. As charged clouds form or pass over a site, changes in the earth's electric field will occur. These can be routinely monitored using 'field mills.' Lightning is the discharge of the charge surplus to the earth or to other regions within the cloud. A discharge to the ground is initiated by downward 'stepped leaders' which ionize channels which subsequently carry upward 'return strokes.' Return strokes carry much larger currents than the stepped leaders and are the principal source of the flash and thunder. Thunder results from the explosion of air heated by the return stroke. Lightning discharges also occur within clouds (intra-cloud) while discharges between clouds (inter-cloud) are infrequent (Uman, 1986). In the temperate zones the preponderance of all flashes are within clouds.

A wide range of specialized instruments is used to collect needed meteorological data. Surface wind convergence is deduced from anemometer networks, electric field behavior from field mills, precipitation from weather radar, and cloud top altitudes from weather radars and satellites. Rapid response optical detectors have recorded lightning spectral pulses in central Florida (Cundiff et al., 1986). Lightning flashes have been counted and their currents measured by networks of detectors intercepting their electromagnetic (EM) radiation. Transportable lightning EM monitors are available, such as

Honeywell's LSZ-850 LSS (Lightning Sensor System) for aircraft protection (Anon, 1988). Flashes or strokes can be located by radio direction finders (giving rise to 'sferics' data bases) and, recently and most importantly, by networks of wide-band, magnetic direction finders or time of arrival systems.

Modern lightning detection and display systems are impressive and extensive, rendering substantial service to scientific and commercial weather programs. A French company, Dimensions, a spin-off of the French national institute for aerospace research (ONERA), produces SAFIR (Anon 1989c). This system consists sensors which are nodes in a network that warns of thunderstorm and lightning hazards over ranges up to 300 km. SAFIR is in operation at the European Space Center in Kourou, French Guiana. In the United States, a company specializing in such devices is Lightning Location and Protection, Inc., (LLP) of Tucson, AZ. The R•SCAN Company participated in a national lightning detection network and evaluated a time of arrival system, LPATS (Lightning Position and Tracking System) for cloud-ground (CG) reporting (Lyons et al., 1988). This system is described (Orville et al., 1983) and its scientific output is discussed in many sources (e.g. Williams and Orville, 1988). Atmospheric Research Systems, Inc., developed LPATS and operates a prototype network in Florida. These networks provide accurate records of strike location, time and strength over ranges of several 100 km.

## 2.2. The Art of Lightning Prediction

Notwithstanding the limited understanding of lightning, its dramatic aspects and potential for damage have led to many attempts to predict when and where lightning will occur. It is worthwhile to briefly discuss two topics. First, the brief review of the physics of thunderstorms given in the previous section leads naturally to consider the measured parameters which might have value for predicting lightning strikes. There is an extensive body of work on thunderstorm statistics and some of the theories advanced for predicting lightning strikes. These provide a benchmark for judging the quality of predictions.

### 2.2.1. Predictive Parameters

Complementary with the physics of thunderclouds there are available many observations that provide some ideas on how to build a prediction technique. Locale and local structures have long been known to 'attract' lightning strikes. Ancient legend observes that sacred locations and plants favored by the Gods were more frequently hit by lightning and therefore Zeus of the thunderbolt favored the oak, an observation confirmed by measurement (Frazer, 1922). Tall, conductive structures (towers, trees, mountains, lightning rods) are associated with frequent lightning strikes. The Empire State Building is hit 20 to 25 times each year (Anon, 1989a). Modern versions of such locale maps of the frequencies of lightning strikes or thunder days are used to estimate the *a priori* probability of lightning strikes at specific locations as shown in Figure 2.2 taken from Uman (1986). Early 'thunderstorm day' data are in Anon (1952) while recent 'flash density' maps are given in Holle et al. (1988).

As described in section 2.1, the thundercloud cross section (Milan, 1963), is a kind of chimney in which air rises vertically carrying smaller particles. Larger particles falling past the rising particles create static charges which build up in the cloud. At ground level air 'converges' upon the base of the thundercloud chimney and this wind convergence is a precursor of thunderclouds (Watson et al., 1987), where the 'convective growth' is 'rooted in the boundary layer' in Florida (Watson et al., 1989a). The taller the 'chimney', the more intense the displacement of charge by stronger updrafts. The taller the thunderhead, the more likely the occurrence of lightning strikes. This has led to the

suggestion that satellite IR maps used to measure cloud top altitudes would be useful in lightning prediction. Overall the spatial distribution of the flashes is related to the cloud charge distribution, the motion of the cloud, and the inherent spatial variability of strikes from a common charge center (Krider, 1988).

The thunderstorm days of Figure 2.2 can be used to make an *a priori* time averaged prediction of lightning strikes. Time averaged predictions of lightning strokes per square mile per year are made using the the mean number of thunderstorm days per year, $N_t$. Observations show that the number of lightning strikes (cloud to ground) per square mile per year is 0.05 to 0.80 times Nt (Uman, 1986). At KSC, where $N_t = 90$, one expects a historical rate in the range of 4.5 to 72 strikes per square mile per year. The range in $N_t$ is modified by topography (for examples see Lopez and Holle, 1986). A historical rate is useful for choosing sites for facilities, but is not useful for adjusting rocket launch operations which are sensitive to weather changes. Other parameters must be taken into account such as local time. Lopez and Holle (1986) show that the preponderance of KSC flashes occur from 1400 to 2000 local time. Locale affects lightning strike maps. In the KSC region, Holle et al. (1988) report an average of up to 15 to 25 flashes per square mile per year based on three years of data.

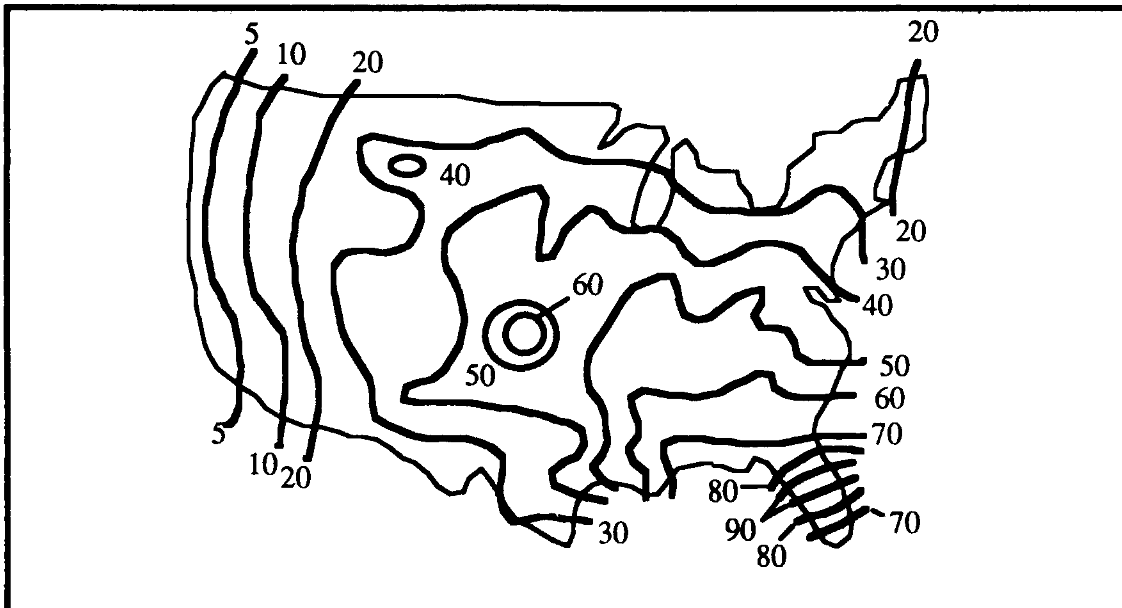


Figure 2.2 Map of Mean Number of Thunderstorm Days, from (Uman, 1986).

The construction of a lightning predictor should use lightning stroke 'precursors' based upon the following topological and meteorological data:

(1) Flow regime (calm, NE, SE, SW, and NW);

(2) Humidity of surface air mass;

(3) Locale and local structure,

(4) Wind convergence;

(5) Altitude of thundercloud tops;

(6) Electric fields at ground level.

It would be encouraging if one or more of these meteorological data sets were used in showing an ability to predict future lightning strikes. This pilot study uses wind total area divergence data to lay the ground work for more sophisticated networks simultaneously using several types of meteorological data sets (see recommendations in Section 5.2.)

### 2.2.2. Predictive Methods

Prediction of lightning strokes has been of two types: (a) a priori predictions based upon historically based, time-averaged behavior, and (b) dynamic predictions which, being based upon current meteorological data, are responsive quantitative predictions. An example of an a priori time averaged prediction has been given in section 2.2.1 in the estimation of the annual thunderstorm days at KSC. Recent work has focussed on more time-responsive predictions using larger and more complex data sets (e.g. radar reflectivity, wind convergence). Some severe storm, thunderstorm, and lightning prediction projects are listed in Table 2.

Austin (1985), citing many of the workers in Table 2.1, gives a guardedly optimistic prognosis for forecasting using pattern-recognition of synoptic data sets. Watson et al. (1987), based upon their 'contingency table', describe their preliminary results as giving a 1 in 2 chance for forecasting lightning based upon convergence (i.e. data gathered from synoptic wind measurement networks). Watson et al. (1987) define a contingency event as "a sustained drop of total area divergence of more than $1.5 \times 10^{-4}\ s^{-1}$ for more than 10 minutes" (see also Watson and Blanchard, 1984) This is a substantial improvement over prediction methods based upon historical rates which do not respond to the immediately previous weather conditions.

Table 2.1 Studies of Thunderstorm and Lightning Relationships

| Individual(s) * | Nature of Project |
|---|---|
| Hu (1963) | First ANS trainable forecasting system |
| Battan (1965) | Associates precipitation amount and flash count |
| Austin & Stansbury (1971) | Located lightning by precipitation events seen on radar |
| Marshall & Radhakant (1978) | Lightning indicated using radar precipitation maps |
| Watson & Blanchard(1984) | Divergence and convective precipitation in Florida |
| Cherna et al. (1985) | Satellite IR/visible data for thunderstorm assessments |
| Watson et al. (1987) | Presents convergence/flash contingency table |
| Holle et al. (1988) | Convergence/stroke data correlations with flow regimes |
| Lampru (1989) | Systematic use of ANS for predicting severe storms |
| Barnes (1989) | Prediction of lightning triggered by a rocket aloft |
| Barnes & Frankel (1990) | Study of ANS trained to predict lightning precursors |

*Two papers which appear to be relevant but of which copies were not obtained are Bent and Llewellyn (1976) and Burke (1990).

Forecasters, using a national lightning detection network, project lightning activity based on viewing maps overlaid with lightning stroke activity which is seen to be moving

with storm fronts (Lyons et al., 1989). Fincher (1988) has speculated that lightning prediction will, in a few years, give flash probabilities by locale and time of day. For the present study, the method of Watson et al. (1987) for predicting lightning strikes as developed for the KSC region will provide a benchmark against which to compare this program's results.

## 3. Training an ANS Predictor

The design of the ANS for the prediction of lightning required our experience with ANS, sources of appropriate data sets, and an understanding of the behavior of neural systems and the physics of thunderstorms. Once the networks were trained, appropriate and accepted evaluation techniques were used to rank networks by type and training level. Lastly, attention was given to the design of the man/machine interface which users must invoke to operate the planned lightning predictor.

### 3.1. Network Modes and the Uses of Data

There are two modes involved in the use of ANS: the training mode and the actual use mode (see Figure 3.1). In the training mode, available data are applied to the network, which then uses learning algorithms to make the desired transformation from inputs to outputs by adjusting the strength of the dynamic links connecting its processing elements.

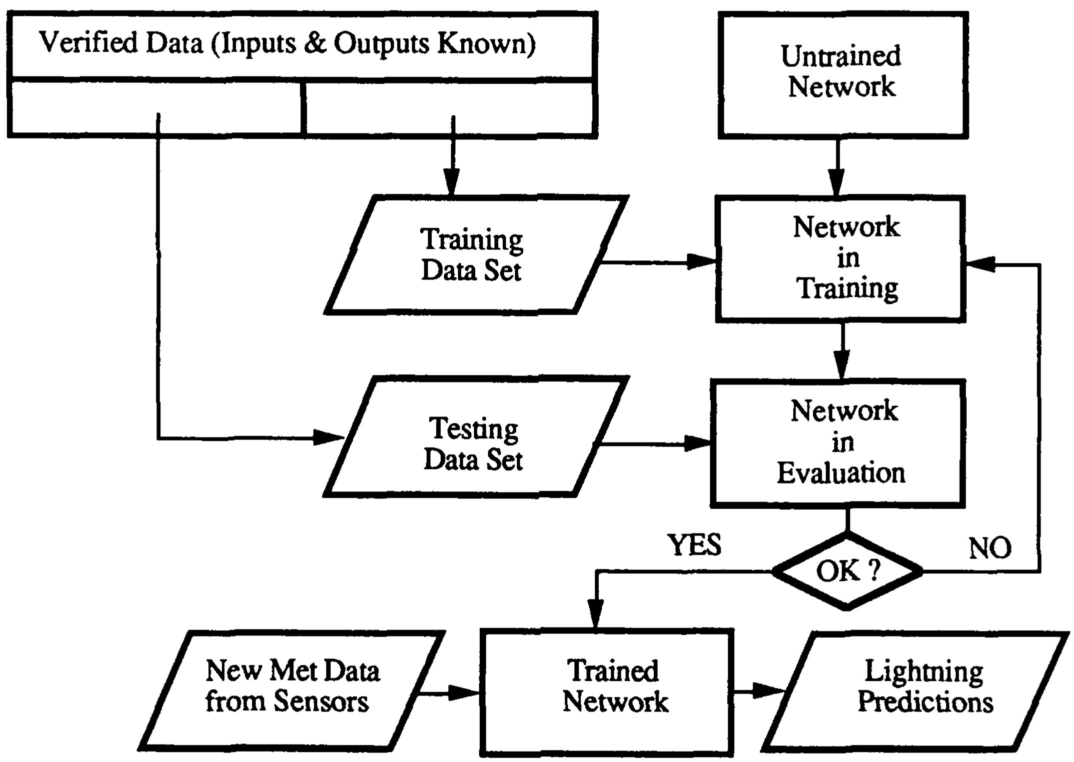


Figure 3.1 Use of Verified (Well-known) Data to Train and Test an ANS for Predicting Lightning Strikes Using Subsequently Obtained New Meteorological Data.

Testing the training effectiveness, before actual use, is part of the training mode. In the actual use mode, the network no longer learns, but rather, it is used to produce outputs based on new meteorological (the 'met data' in Figure 3.1) inputs. Training periods may be interspersed with testing periods as the availability of new met data permits.

During training it is important to keep in mind that data play two different roles in the ANS as seen in Figure 3.1. The first role data play is as input (stimuli). Inputs used during training should be those which are expected to be available when the network is in actual operation. The second role for data is as output (responses) during training. In the backpropagation learning scheme, these outputs are referred to as "target values". During training, the target value data are used to "teach" the network the output response desired for a given input. In this study, two different types of data were chosen for use as target values which resulted in two distinct ANS predictors. First, the occurrence of high electric field was used as target value, as an indicator both of cloud to ground strokes (Christian et al., 1989) and as a warning of the danger of triggered lightning (Uman, 1988). Second, LLP data were used to 'teach' the network to recognize cloud to ground strikes.

Therefore, our ANS predictors were divided into two groups according to the 'training data' chosen (see Table 3.1): (1) electric field predictors, and (2) cloud to ground strike predictors. An ANS trained to predict cloud electrification would be of value for quantifying correlations with the input data. On the other hand, the dangers cloud to ground strikes present to ground personnel, fueling operations, etc., recommended that this study concentrate on 'training data' (i.e. ANS training 'target' values) consisting of cloud to ground strikes. Therefore, though it might be harder to attain, an ANS trained to predict cloud to ground strikes received the emphasis in this study.

Table 3.1. Some Possible Combinations of Network Inputs and Training Data

| INPUTS | TRAINING DATA |
|---|---|
| Wind | Electric Field |
| Wind | LLP |
| Wind, Electric Field | Electric Field |
| Wind, Electric Field | LLP |
| Wind, Divergence | Electric Field |
| Wind, Divergence | LLP |
| Wind, Divergence, Electric Field | Electric Field |
| Wind, Divergence, Electric Field | LLP |

Input data for the network could include the wind data, the electric field data, nearby LLP data and 'products' of these or other data. 'Products' refers to results of

processing the raw data in some way to derive a presumably superior quantity. One such product which has been shown to be of value is the wind Total Area Divergence (Watson et al., 1987). This product has been shown to predict 50% of cloud to ground strokes at KSC. The first ANS we tried used only the raw wind data as inputs. Later networks will include the divergence as input.

## 3.2. Data Sets

The primary meteorological data obtained from the Kennedy Space Center (KSC) are the measurements of the Wind Mesonet, the Launch Pad Lightning Warning System (LPLWS) and the Lightning Location and Protection System (LLP). The first two of these systems consist of arrays of sensors covering the entire KSC area. The three LLP system sensors are located outside KSC and cover a much larger area, of which KSC is a part. All of these data have been recorded and archived on a regular basis by a private contractor, currently Computer Sciences Raytheon, Meteorology Section (CSR/Weather). Volumetric radar scans and satellite imagery for the KSC area exist, but their use is beyond the scope of this pilot project. Table 3.2 summarizes the data available for this pilot study.

Table 3.2. Weather Data Available for this Study.

| Sensor System | Data Type | Data Availability | Data Rate |
|---|---|---|---|
| Wind Mesonet | Wind Direction | 12, 30, 35, 54, 60, 162, 204, 275, 295, 394, 492 feet | 5 minute average |
| | Wind Speed | 30, 35, 54, 60, 162, 204, 275, 295, 394, 492 feet | |
| | Temperature | 6, 12, 54, 162, 204, 492 feet | |
| | Dew Point | 6, 12, 54, 162, 204, 492 feet | |
| | Barometric Pressure | 6 feet | |
| | Humidity | 6 feet | |
| LPLWS | Electric Field | 31 sensors at ground level | 3-5 samples at 10 Hz |
| LLP | Lightning Flash Latitude, Longitude | Southern Florida | irregular 7500/hr max. |

The Wind Mesonet consists of an array of sensors mounted at various altitudes on utility poles or other available structures. These sensors measure wind speed, wind direction, dew point, humidity, barometric pressure and temperature. Most of the 53 speed and direction sensors are at 12 and 54 feet above the ground. Temperature is measured primarily at 6 feet and 54 feet. These wind data are measured several times per second, but only the five minute average values are available in the archives.

The hypothesis upon which the lightning prediction methods used as benchmarks here are based is that thunderstorms induce dramatic changes in wind flow patterns. The value of wind data can be appreciated by considering the work of Watson et al (1987). In their work, a "product" of raw wind data has been derived and shown to have value in predicting lightning strokes. This product is called the 'Total Area Divergence'. It is a measure of the rate at which wind is flowing out of the KSC area. The relationship between the Total Area Divergence (i.e. the wind field) and thunderstorm electrical activity (i.e. electric fields) is schematically illustrated in Figure 2.1. In this figure the surface winds are shown flowing in (a negative Total Area Divergence) toward the base of the thundercloud. This air mass subsequently rises vertically leading to charge separation and charged regions which lead to the vertical electric fields shown in Figure 2.1.

At this date, total Area Divergence is the best single lightning predictor available at KSC at this time. Our results are compared with those of Watson (1989c) who provided us with data tape containing his calculations of the Total Area Divergence for the period we have studied. We have recommended that Total Area Divergence be among the inputs to the version update of this ANS.

The LPLWS system consists of 31 sensors, often referred to as 'field mills', which measure the vertical component of the local electric field. If properly placed away from metal structures on the ground, the data from these sensors should give a good indication of the existence of cloud electrification overhead. Cloud electrification data have two values. First, they provide a near-term warning of the danger of cloud to ground strokes. Second, they are an indication that aircraft and rockets launched into those clouds may trigger lightning. When examined in detail and compared with each other, these data can also be used to locate nearby cloud to ground lightning flashes.

The LPLWS sensors sample the electric field at 10 Hz, but since the installation of the Cyber 860 computer system at KSC in 1985, only 3-5 samples per second have been archived. Even at the reduced data rate, the volume of LPLWS data makes it impractical to store all of the data indefinitely. Periodically, the volume of stored data is reduced by KSC personnel. All data are discarded except during periods beginning three hours before and ending one hour after the issuance of a Meteorological Watch Advisory. During a visit to KSC in February, 1989, it was learned that the last time this had been done was May, 1988. Therefore, as 24 hour data were still available after May 1988, data during the succeeding summer, in July 1988, were used in this study.

The LLP data are derived from three magnetic direction finders which respond to cloud to ground lightning strokes. The strokes' latitude and longitude are determined by triangulation. These data cover most of southern Florida and capture an estimated 80% of all flashes (MacGorman and Rust, 1988, Barnes and Metcalf, 1988). The LLP system does not respond to intra-cloud lightning, nor to strokes which have a large horizontal component in their path to ground.

After consultation with NASA personnel, the Air Force Air Weather Service and CSR/Weather, a two week period was chosen during which there were archived data of all three types for days when there was thunderstorm activity and for days when there was none. This period was July 12 to July 27, 1988. On some of the data tapes, these days were denoted by their Julian Day sequence number: 88194 to 88214. In the Julian system, January 1, 1988, would be 88001 and December 31, 1988, would be 88366.

## 3.3. Preprocessing

As with any project which involves analysis of field data from another facility, significant effort was required to edit the data and put it into the proper form for analysis. The cooperation and able assistance of CSR/Weather, NASA and Air Force personnel were essential to the completion of this phase of the project.

The Wind Mesonet data and the LLP data can be obtained from KSC on tape in ASCII (American Standard Code for Information Interchange) format. In this form, the data can be examined by any text editing software. The LPLWS data are voluminous. In ASCII format, a single day's data occupy eleven 9-track tapes. On the other hand, in binary form (computer internal representation) the storage of one day's data requires only one tape. Binary format is thus the form of choice for the LPLWS data. Of course, in this form, the data cannot be examined by word processing software.

Use of the LPLWS data was complicated by several factors. The least difficult of these to deal with was the fact that the Cyber computer with which they were processed at KSC uses 12-bit bytes and 60 bit words, while the Macintosh uses 8-bit bytes and 16 or 32 bit words. Much more difficult was the fact that the Cyber computer system inserts a variable number of housekeeping words at various (unpredictable) points in the data on tape. Failure to allow for these words results in incorrect reading of the data.

The KSC weather data are stored on 9-track magnetic tapes. The data are not arranged in the standard tab-delimited form which the LightningLynx©[1] system requires its data to have. Therefore, stand-alone applications have been developed which convert from binary to ASCII form as necessary and reformat the data into the tab-delimited form. To facilitate their use the data processing system includes a Qualstar model 1054 9-track tape drive. This model is equipped with a standard SCSI (Small Computer System Interface) connector which allows direct transfer of tape resident data to the Macintosh IIx internal disk drive. The 9-track tape drive and the conversion applications with the LightningLynx© ANS system comprise the Geophysics Laboratory lightning predictor system.

## 3.4. Wind/Lightning Networks

The ANS networks used are three-level backpropagation designs as described in Rumelhart and McClelland (1986). The number of input nodes is determined by the arrangement of the types and amount of meteorological data sets chosen for training the network. In this study 106 input nodes are typically used. The hidden layer nodes are minimized - within the constraint that network performance is not critically limited. Lastly, 64 output nodes were used, corresponding to 16 lightning strike areas (which are termed 'tiles' here) each with 4 time intervals for prediction. At KSC there are 16 square tiles each of which is 4.58 nautical miles on a side. The total field covered by the 16 tiles is 21 nautical miles on a side.

The networks are designed to be trained to the correlations among a variety of meteorological events. Two types of networks were studied: (1) surface winds to electric fields (E Fields), and (2) surface winds to lightning strokes. The data used have a direct

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1 "LightningLynx©" is a copyright of KTAADN, INC., reserved 1990

effect on the network layout, i.e. the number of input, hidden, and output nodes. Because of the meteorological sensor arrangement at KSC, the networks used here typically possess 106 input nodes as determined by the wind tower grid. They possess a varying number of hidden nodes as determined by the performance requirements. Lastly, these networks use 64 output nodes corresponding to the 4 time windows for the 16 areas ('tiles') defined for the KSC region in this study, see Figure 3.2.

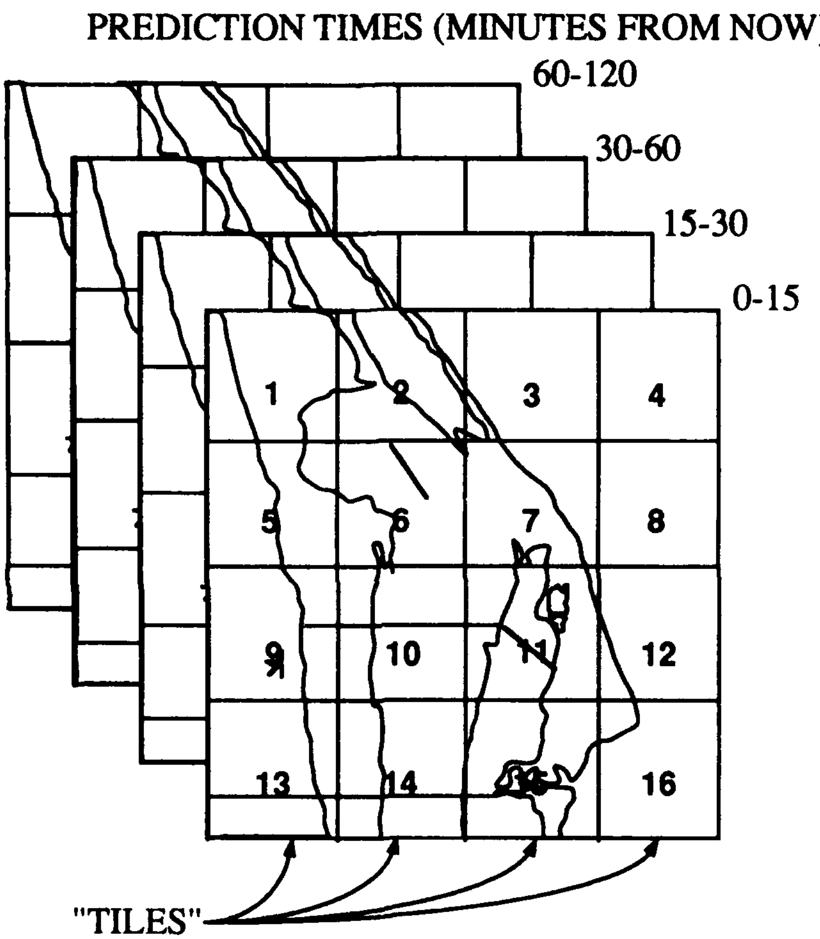


Figure 3.2 Tiles and training periods used in this study. One network output node is assigned to each of these 64 tiles.

ANS training reduces output errors (defined as the difference between actual and required responses) by a steepest descent method. Training proceeds in a sequence of 'passes' each of which starts from the level of learning achieved during the previous pass. The metric used in this method is a summary 'pass error', defined here,

$$\text{Pass Error} = \Sigma_T \{\text{network output - target value}\}^2 \tag{3.1}$$

where the summation ranges over all data samples and all output nodes. Generally, the pass error decreases toward an asymptotic level as the network approaches its maximum

performance. If better performance is required, networks with more hidden nodes can be formed and trained.

The first ANS constructed used the raw wind speed and direction as inputs and the electric field as output. For each wind sensor, the wind speed and direction were used to generate two network inputs: the wind components in the north and east directions. This network was trained to predict electric field values exceeding 500 V/m at the ground. Data used were from July 18, 1988. An important result of working with this combination of data was that a three layer backpropagation network with fewer than 70 hidden layer nodes would not converge to a stable state, while one with 70 hidden nodes would learn stably.

The number of hidden nodes is usually felt to represent the 'features' in the physical process under study. That is there appear to be a number of approximately 70 features connecting the wind field with the electric field. Several approaches might be used to reduce the number of hidden nodes. For example, if the wind divergence is more directly connected to the electric field, then use of divergence might usefully reduce input and hidden nodes and reduce the training time required.

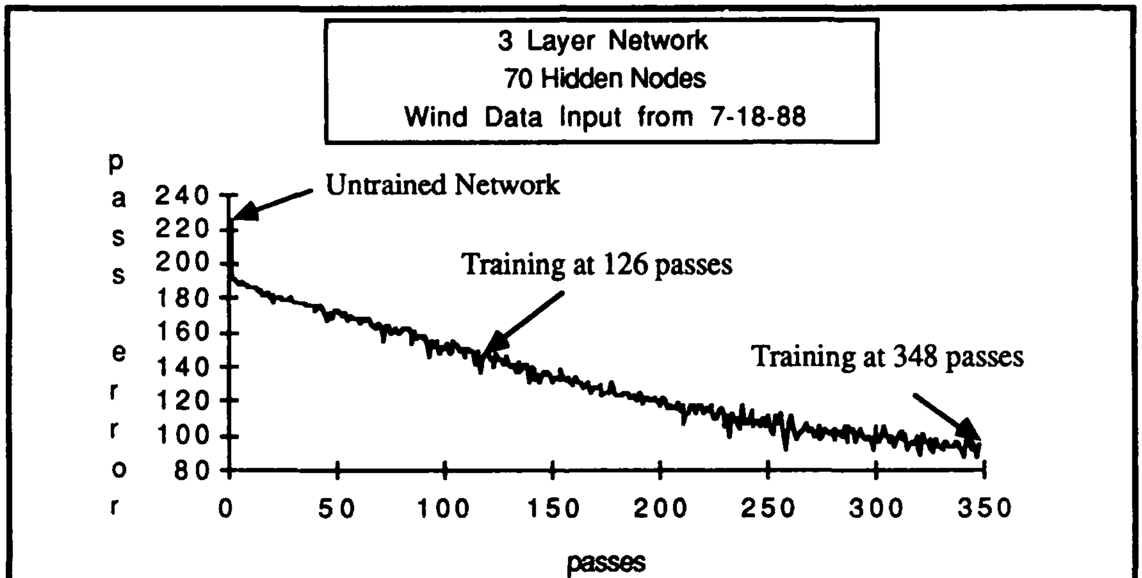


Figure 3.3 Training History for a 106/70/64 network using wind as input and electrical field as target value. As Pass Error Approaches a Constant Value Training is Completed.

The pass error history for a 106/70/64[1] network is shown in Figure 3.3. Here history is given in the number of network training passes the network underwent. On the Macintosh IIx each pass required about 4.5 minutes. The overall decrease in pass error is indicative of continued improvement of the network performance with each succeeding pass. Note that the network training was stopped at pass 126 for testing at one level of performance and later resumed to achieve better performance (i.e. lower pass error). This shows that predictive ANS may be intermittently trained at higher performance levels as new weather history is presented. When training with fewer hidden nodes, even as many

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[1] This terminology is "input node number/hidden node number/output node number"

as 65, oscillations in the pass error were seen while no substantial reduction or improvement in network performance.

The second ANS type used the wind data for input as before, but used LLP data of cloud to ground lightning strokes to assign target values. Since very few cloud to ground strokes occurred on July 18, 1988, data from July 24 and 25 were used for training these networks. Remarkably, much smaller networks could learn stably when LLP data were used for assigning target values. The smallest such net had only 6 hidden layer nodes.

The training and evaluation of a large number of networks was required to reduce the results to those given here. A major improvement in the wind field to lightning strike ANS predictor performance is expected when larger sets of weather (numbers of days for the same weather regime) are used. Another improvement is expected when network layouts include several input data types simultaneously (e.g. wind, electric field, satellite cloud top altitudes, and others).

## 3.5. Network Interface

A network interface, sketched in Figure 3.4., helps evaluating alternative layouts for ANS predictors. Users of the projected system must deal with several complex entities: extensive data bases, training and retraining large ANS and the evaluation of

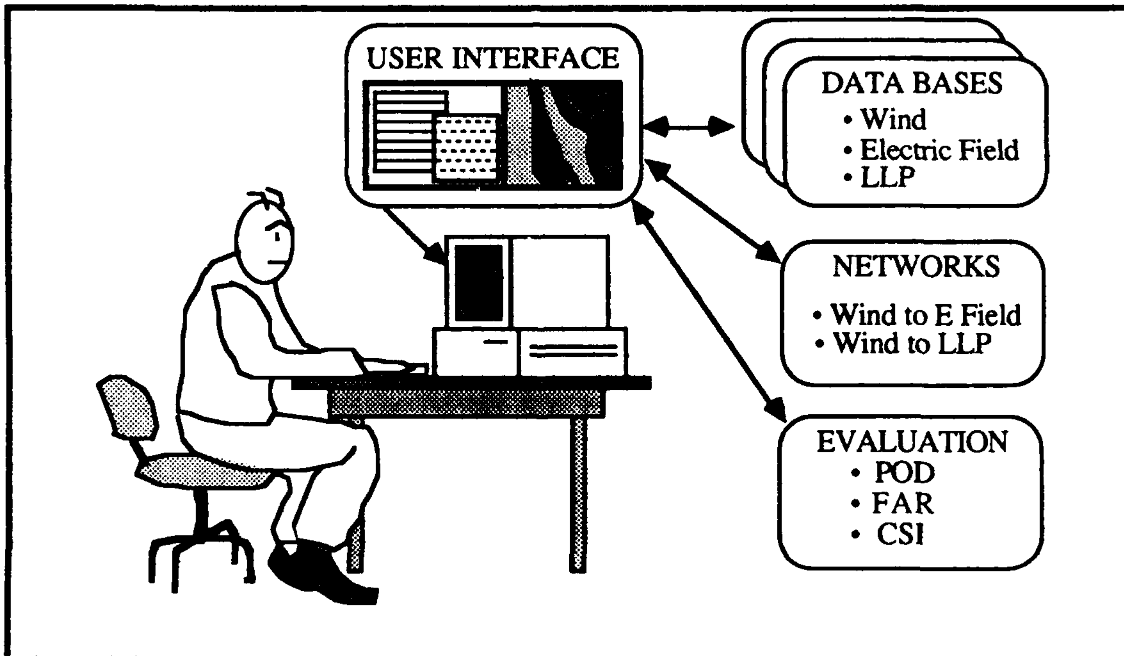

Figure 3.4 Lightning Predictor User Interface Showing its Three Principal Functions

performance using accepted statistical concepts. These jobs are handled on a Macintosh IIx desktop computer through a comprehensive man/machine interface prepared in this study. The interface is a screen presentation system which provides the following features:

(1) Convenient program interaction through the use of windows, menus and mouse,
(2) Direct access to large data sets,
(3) Creation, training and retraining of alternative ANS designs, and
(4) Presentation of ANS predictions with standard evaluation measures.

This lightning prediction system is called LightningLynx© and it is built on the Macintosh IIx computer with a flexible user screen (see Figure 3.4). A 'bare bones' (Version 1.0) of the interface is provided. The LightningLynx© interface adheres to Macintosh standards

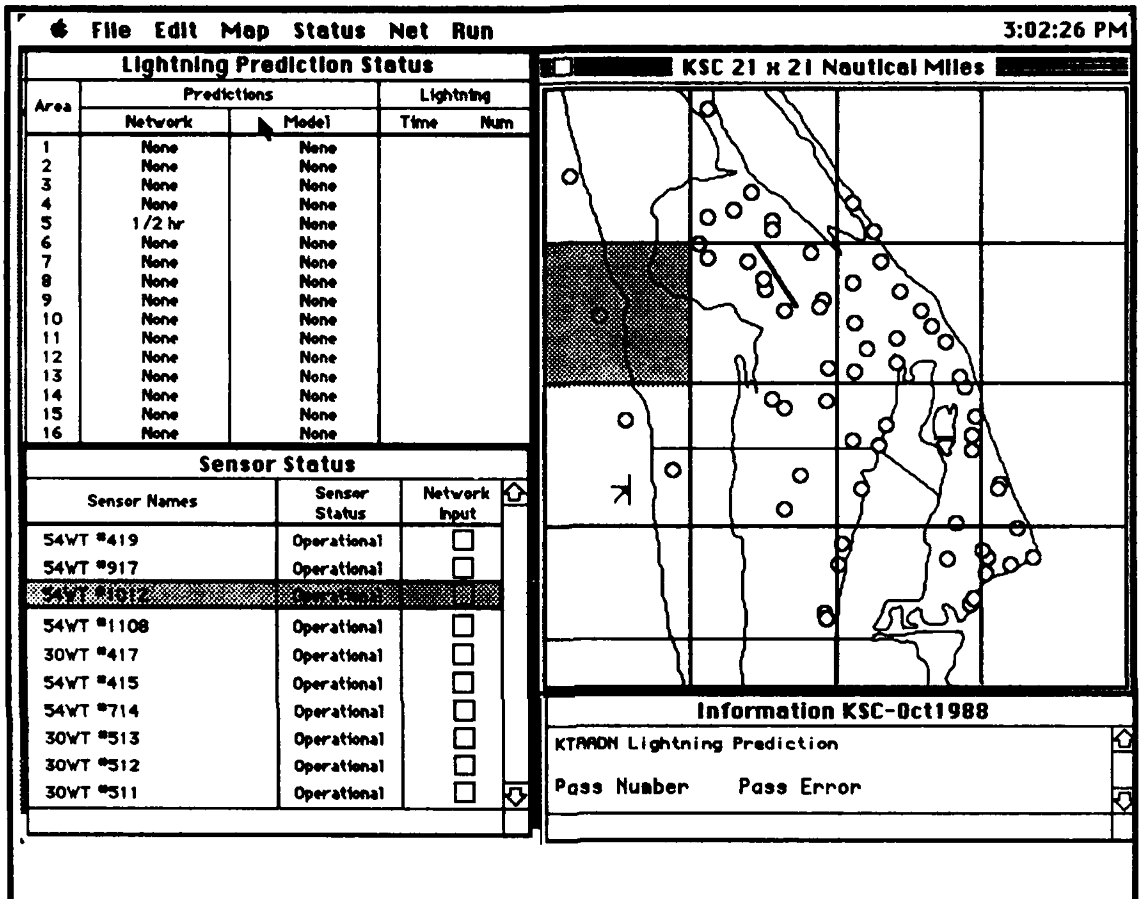


Figure 3.5. Lightning Prediction Screen Display with Its Windows as the User Sees.

via a conventional Macintosh windowing system. The user, with keyboard and mouse, can gain access to data files, networks and evaluation methods and then initiate training or testing runs. The user, through the interface, can request data files of the following types:

(1) Meteorological data sets (wind, electrical fields, etc.),
(2) Networks (general types and specific trained networks), and
(3) Network performance output files

The interface software allows the user to create new networks for training. Networks may be saved on magnetic media at any stage of training through a menu item. Catalogues of ANS predictor systems can be built for various weather regimes at a particular site. Saved networks may be recalled, again through a menu item, and trained further or used as is for lightning prediction. It is expected that user comment will aid further interface development.

# 4. Network Scoring

Appropriate and accepted evaluation techniques are used to rank the performance of the trained ANS used in lightning prediction. These are presented and applied to a range of trained ANS predictors in the following sections.

## 4.1. Evaluation Method

Evaluation of networks in various stages of training must be carried out using a rigorous, well-accepted methodology. The "receiver-operating-characteristic" (ROC) graph (Green and Swets, 1966) provides such a technique. The ROC graph is based upon a 2 x 2 stimulus-response matrix such as pictured in Figure 4.1 in which the known stimuli are row entries and the perceived response options are column outputs. The capital letters (A, B, C, and D) represent the total number of times each type of event occurred. For example, A is the total number of times a lightning stroke occurred in a specific tile in a specific time frame as it was predicted to occur. The conditional probabilities (e.g. $P(Y|y)$) are shown underneath these total numbers of specific occurrences given by the names underneath the conditional probabilities.

Predicted Alternative

| Observed Alternative | Predicted: yes | Predicted: no |
|---|---|---|
| yes | A<br>$P(Y \mid y)$<br>Hit | B<br>$P(N \mid y)$<br>Miss |
| no | C<br>$P(Y \mid n)$<br>False Alarm | D<br>$P(N \mid n)$<br>Correct Rejection |

$P(Y|y) + P(N|y) = 1$ and $P(Y|n) + P(N|n) = 1$

Figure 4.1 Stimulus-Response or 'Contingency' Matrix for Evaluating Networks

The upper left-hand box gives the conditional probability of the network responding that lightning will occur when it actually occurred. The lower right-hand box is the conditional probability of the network responding that lightning will not occur in a situation in which it indeed did not occur. A good lightning predictor would have high probabilities in these two boxes. The lower left-hand box is the probability that the network would

predict lightning when it did not occur - the probability of a false alarm (PFA). The upper right-hand box is the probability of predicting no lightning when it did occur.

A decision evaluation system can be built on conditional probabilities. P(Y|y), the probability of the system predicting Y given that y is observed. The probability that the decision system response is Y to weather stimuli, y, applies to the period, t to t+dt, and some specified area, da. If Y is not the response we must choose N. For this reason the two equations hold:

$$P(Y|y) + P(N|y) = 1 \quad \text{and} \quad P(Y|n) + P(N|n) = 1 \qquad (4.1)$$

This allows one to plot all the consequences of the decision making on a two degree of freedom graph, the ROC graph which is pictured in Figure 4.2.

In evaluating lightning detection networks the behavior of the output nodes is used as a scoring measure. An output node 'activation' level, $\alpha$, will vary from 0.1 (event predicted not to happen) to 0.9 (event predicted to happen). A threshold T has been adopted for decision making. If the activation level of an output node is greater than T, $\alpha > T$, the positive prediction Y is declared; otherwise, $T > \alpha$, a negative prediction N is declared. When evaluating the network, all predictions are compared with the known results (i.e. observations) y and n in a contingency matrix (see Figure 4.1) as T varies.

Even in high activity regions, lightning strikes are rare. It is important for the prediction scheme to correctly predict non-lightning events which numerically dominate stroke 'events'. A lightning predictor would have a high overall correct percentage if it always predicted 'no strike'. This is the 'play the winner strategy' (Stanski et al., 1989). The successful predictor must predict the numbers of *lightning* events. So while a low false alarm rate is desirable, it is not indicative of predictive power when true alarms are rare.

Measures of performance are adapted based on the following definitions taken from the contingency matrix of Figure 4.1 (Stanski et al., 1989) from which the following performance measures can be defined,

$$\text{Probability of Detection, PoD} = A/(A + B) \qquad (4.2)$$

$$\text{Probability of False Alarm, PFA} = C/(C + D) \qquad (4.3)$$

$$\text{Miss or Probability of False Dismissal, PFS} = B/(A + B) \qquad (4.4)$$

$$\text{False Alarm Ratio, FAR} = C/(A + C) \qquad (4.5)$$

$$\text{Correct Rejection} = D/(C + D) \qquad (4.6)$$

The difference between the Probability of False Alarm PFA defined in Eq. (4.3) and the False Alarm Ratio FAR in Eq. (4.5) is significant. The PFA is the conditional probability of (false) positive prediction given that the event was not observed. On the other hand, the FAR is the ratio of false predictions of the event to all predictions of the event. The FAR measure is only sensitive to predictions and is a good measure of the system performance only when false alarms are very undesirable. On the other hand, the PFA is a better measure of the likelihood of the actual events and should be used for decision making.

Two success and skill measures are used. The Critical Success Index (CSI) introduced by Donaldson, et al., 1975, is a measure of relative accuracy since it shows the ratio of predicted cases vs. both predicted and/or observed cases,

$$CSI = A/(A + B + C) \tag{4.7}$$

The range of CSI values extends from 0 to 1. CSI differs from FAR and POD because it is sensitive to both false alarms and missed events. To evaluate the performance of the network the Heidke skill score is used (Stanski et al., 1989). The Heidke skill score values range from $-\infty$ to $+1$. Plus one indicates the perfect score and zero means that the number of correct predictions equals the number of expected correct predictions. Thus the skill "subtracts" the number of correct predictions which would have been obtained merely by chance.

$$Skill = [A + D - (Yy + Nn)/M]/[M - (Yy + Nn)/M] \tag{4.8}$$

where M is Total Number of Observations:

$$M = A + B + C + D \tag{4.9}$$

$$Y = A + C \tag{4.10}$$

$$N = B + D \tag{4.11}$$

$$y = A + B \tag{4.12}$$

$$n = C + D \tag{4.13}$$

The values in the contingency table of Figure 4.1 are used to compute conditional probabilities in a receiver operating characteristic (ROC) graph illustrated in Figure 4.2. Overall network performance depends on the value of the threshold, T, chosen by the user. If T is large then fewer events will be classified as lightning strikes, decreasing PoD and PFA at the same time. That would be indicated by a point in the lower left side of the ROC graph of Figure 4.2. Small T will lead to high false alarm rates in the upper right-hand corner of the graph. For a given network the ROC is a curve between these two extremes. Setting T is the responsibility of the user who must balance the benefit of a correct prediction against the cost of a mistake.

When the probability of detection is equal to the probability of a false alarm the decision-making process is doing no better than it would by guessing. This situation is shown by the straight line c in Figure 4.2. For a lightning prediction system, one expects that curve c would be the performance of an untrained network. Increasing levels of training are shown by the curves a & b which move toward the upper left-hand corner of the graph. For a given level of training and a series of threshold values ($T_1$, $T_2$, and $T_3$), one can estimate the ROC curve as shown by b in Figure 4.2. The integral under the ROC (the shaded area) is a measure of the network's performance. For c the shaded area is zero corresponding to chance predictions or 'shooting in the dark'. To find an optimal threshold, $T_O$, the user must estimate the benefits and losses of correct and incorrect predictions, respectively. Having trained a network, one adjusts thresholds until the best balance is struck between these benefits and losses. An important ANS feature is that, with the resumption of training, skill level might be incrementally increased at a local

observation site. It is important to consider the overall process of retraining and resetting thresholds in the ultimate local user's interface to the processor.

The scoring of the present lightning predictor contains some elements adapted to the geography and future time intervals of interest for KSC. The geographical breakdown for KSC is shown in Figure 3.4. For each geographical subdivision, the network has been set up to predict lightning activity in four future time windows. Prediction for the interval from the present to 15 minutes in the future is called the 'nowcast.' Predictions for the interval from 15 minutes to 30 minutes is called 'Time 1/2'; between 30 minutes and 1 hour is 'Time 1'; and between 1 hour and 2 hours is 'Time 2'. Statistics for each prediction window are separately compared with each time in the future.

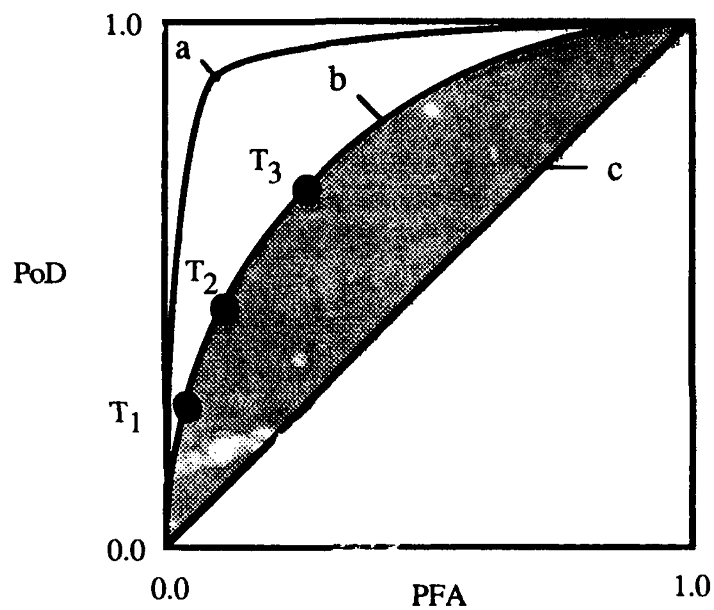


Figure 4.2 ROC Graph Showing the Predictor's Performance at Several Thresholds ($T_1$, $T_2$, and $T_3$) at one Level of ANS Training, b, among Several Levels (a, b, and c).

The scoring system is conservative. In the event that the network predicts lightning activity for 'Time 1/2' and no lightning stroke occurs in the 'Time 1/2' window the network scores zero.. This is so even if subsequently a lightning stroke occurs for that geographical region at 'Time 1'. Generally, the scoring gives the predictor lower performance scores than were it credited with subsequently observed strikes for any of its time windows as it is penalized for predictions which are 'too early' or 'too late.' Predictions for specific time intervals and tiles are used to construct contingency tables as the basis for comparison with alternative lightning prediction systems.

## 4.2. Predictor Performance

The literature on the performance of mathematical correlation schemes for predicting lightning includes the work of Watson and Blanchard (1984) which associates lightning

with wind convergence. A quantitative method of Watson et al. (1987) is used in this study. Essentially, a lightning strike is predicted when wind divergence is less than $-1.5 \times 10^{-4}$ $sec^{-1}$ for at least 10 minutes in the KSC area. This criterion was used by Watson et al. (1987) to create a contingency table and will be used as a benchmark for judging the results obtained here using ANS lightning strike predictors.

The lightning strike predictions of this study are compared with the results of Watson et al. (1987) in Table 4.3 expressed in the scoring parameters Section 4.1. Lightning prediction using ANS is shown to reach a performance level comparable to that obtained by Watson et al. In addition, it is important to establish that the assumptions and measurement conditions of the Watson et al. (1987) study and this study are sufficiently similar. This comparison is shown in Table 4.4 where it is seen that the parameters of the two studies are sufficiently alike. In conclusion, the predictions obtained using trained artificial ANS (as a means for building a lightning flash predictor) and the predictions provided by the state of the art are close in overall performance measures.

Table 4.3 Comparison of the Results of Watson, et al. (1987) and Those of this Study.

| Performance Measure | This Study | Watson, et al. (1987) |
|---|---|---|
| Probability of Detection | 0.41 | 0.47 |
| Probability of False Alarm | 0.57 | 0.56 |
| Critical Success Index | 0.26 | 0.29 |

Table 4.4 Similarities and Differences of the Two Studies

| **Aspect of Study** | **Watson et al.(1987)** | **This Study** |
|---|---|---|
| Period Studied | 42 Days in 1983 | 7/24,25/88 |
| Prediction Area | Mesonet | 16 Tiles 21x21 sq. nmi. |
| Wind Sensors Used | 54 feet | All |
| Data Period | 5 minute | 5 minute |
| Predicted Value | c-g flashes (LLP) | c-g flashes (LLP) |
| Prediction Correct If | Convergence precedes flash | Flash time and tile correct |

The reader may be interested in noting the steps in improvement of one of the artificial neural systems toward the performance figures seen above in Table 4.3. The results of Table 4.3 were obtained using one day's raw wind speed and direction data as training input to the networks and a different day's wind data for testing the network's predictions. Shown in figure 4.4 is a ROC plot of the Probability of Detection vs. False Alarm Rates for predicting lightning using networks trained and tested on the same and on different lightning days. The open symbols are for incompletely trained networks (pass error decreasing rapidly) while filled symbols are for completely trained networks (pass error decreases slightly with further training). As the data considered are located in the lower left hand side of the ROC plot only part of the plot is shown. One result is that the steep (at 45 degrees) straight line c of Figure 4.2 is shown by the slightly sloped straight line in the lower part of Figure 4.4.

The training behavior reveals several aspects of using an ANS for prediction. Consider a network trained on one day and tested on another day's data (triangular symbols). Performance improvement is seen in the upward movement of the PoD from 'slight' training (open symbols) to 'full' training (black symbols) in Figure 4.4 while PFA increases proportionately less (the black ramp at the bottom of the figure is for equal rates of increase in PoD and PFA). It is expected that as more is learned about building lightning predictors using ANS more performance improvements will be realized.

The apparently better performance in Figure 4.4 when training and testing on the same day's data (square symbols) results from an unacceptable procedure. A single day's meteorological data contain a certain amount of idiosyncratic events (e.g. turbulence) that do not represent the underlying behavior of lightning strikes. To eliminate such an illusion of good performance, ANS predictors must always be tested on different data. At present the 'predictive parameters' of Section 2.2.1 are not used as ANS inputs requiring that the training and testing data be taken from similar 'flow regimes' and so forth. Eventually, ANS predictors will account for these conditioning effects automatically in the inputs.

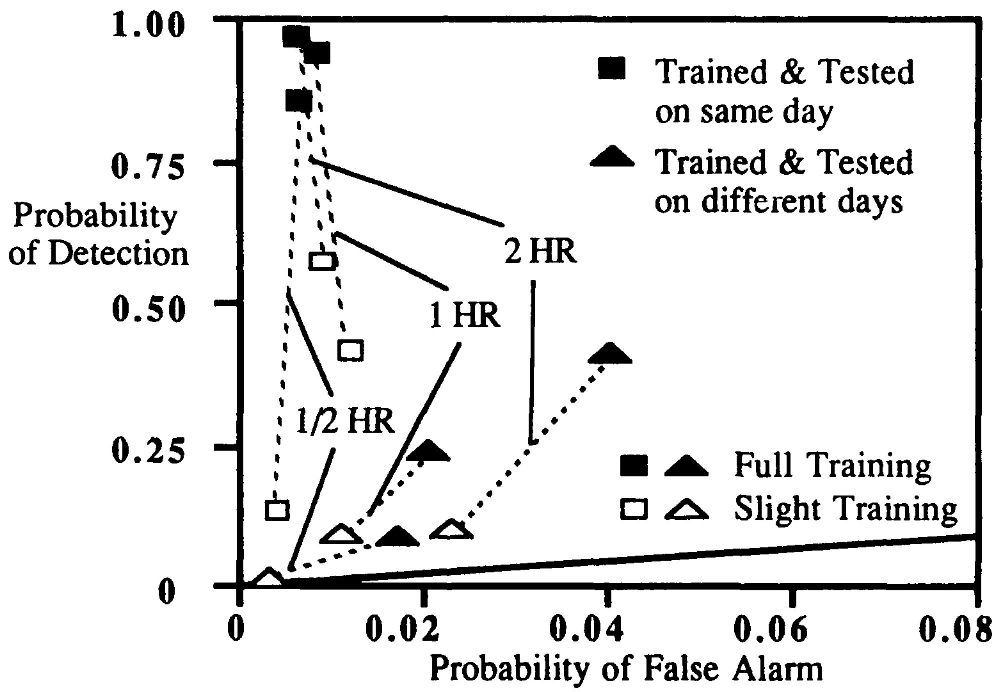


Figure 4.4 Improvements in ANS Lightning Predictor Performance as Training Time is Increased. Testing Across Different Days has the Effect of Testing for ANS Networks which Exhibit Some Valid Mapping of the Underlying Correlations Between the Chosen Inputs and the LLPWS Target Values.

It is expected that significant further improvement in predictor performance can be obtained. Synthesis of different types of data is one of the strengths of the ANS approach. Network predictive power can be expected to increase when other inputs (e.g. electric field, wind divergence, temperature, humidity and radar returns) are included in the input array. Predictive power is also expected to improve when more than one day's data are used in training. Recommendations for improving lightning predictors are given in Section 5.

# 5. Conclusions

This study investigated the possibility of using field data for specifying and training an ANS which can be used to forecast severe weather events, specifically the occurrence of lightning strikes. Comparisons have been made with earlier methods based upon correlation of wind divergence with the later occurrence of a lightning flash. Using KSC meteorological data for wind and lightning strikes a state-of-the-art skill level prediction performance has been attained. Given the complexity of lightning strikes, the current results should be understood as indicative of a promising initiative and cannot be considered definitive. Thus, recommendations are made for further investigation.

## 5.1. Accomplishments

Training ANS for forecasting severe weather events has required that a series of steps be taken to present a reasonably rigorous evaluation of the program goals. The main subtasks undertaken and completed are:

(1) **Data Reformatting** - Reformatting massive weather data sets for input to ANS has been carried out. The data sets on winds, electric fields, and lightning strokes were supplied by KSC personnel The reformatting software was developed at KTAADN, INC.

(2) **Predictor Performance Evaluation** - A predictor performance evaluation scheme was created based upon well-accepted procedures useful for evaluating decision making processes.

(3) **Trial Networks** - A family of ANS was created and adapted to the geography of and relevant time scales for KSC.

(4) **Storm Physics** - Consideration was given to the physics of severe storms and lightning as a basis for constructing prediction networks.

(5) **User Interface** - A user interface for invoking the needed items and functions for building ANS was devised. This interface provided the following functions: (i) entering reformatted weather data sets, (ii) constructing and subsequently training ANS predictors, (iii) evaluating the network skill levels using accepted comparison techniques.

(6) **Increased Skill Levels** - Training of ANS to significant skill levels was carried out for the prediction of lightning based upon wind fields. The networks trained in this project delivered a prediction performance which compared favorably with the performance described by Watson et al. (1987).

(8) **Incrementally Retrainable Weather Event Predictor** - The training of the networks has been stopped and restarted with no observable loss in the previous level of network performance. This feature is a major advance over procedurally programmed predictors which often require fundamental reprogramming when improvements are integrated into the software. Using the

user interface developed in this study, a meteorologist could resume training of the predictor by introducing a new data set without needing to know a high level programming language (such as FORTRAN.)

(9) **Turnkey Macintosh IIx Predictor Workstation with User Interface and Data Files** - A prototype operating lightning predictor workstation has been built with basic functionalities in place.

In sum, this study has provided the following components of an ANS-based 'LightningLynx©' computer man/machine interface program for training lightning predictors in the KSC environment:

A) Documentation

i) Final report

B) LightningLynx© Software

i) LightningLynx© interface software (source code)

ii) Backpropagation learning run time library (machine code only)

iii) CyberMac and LLP Plotter software developed during the contract period for reformatting KSC data tapes

iv) Data and network documents created during the contract

C) Hardware

i) Macintosh IIx computer

ii) Apple Color Monitor with stand

iii) Qualstar model 1054 9-track tape transport

iv) Keyboard, mouse and cables for items 1-3

## 5.2. Recommendations

This examination of the use of ANS for predicting weather events recommends several major areas for research and development,

(A) **Use of Larger Data Sets for Improving ANS Predictor Performance** - Larger data sets of single meteorological inputs would be examined. This task would investigate ANS trained with large data sets:

(a) Larger wind field and LLP data sets

(b) Larger electric field and LLP data sets

(B) **Use of New Combinations of Data Sets and Collateral Data for Improving ANS Predictor Performance** - Watson et al. (1988) state that "Only through the integration of all the data bases available can the forecaster make the best possible prediction." This task would address ANS networks which provide for combining different meteorological data sets. Both ANS layouts which fuse different types of inputs and ANS training using combined sets of field data would be carried out. Issues addressed in this task would improve performance by better utilizing:

(a) Optimum ANS layouts for fusing meteorological data

(b) ANS predictors trained using wind and electric field inputs with LLP data

(C) **Use of the Physics of Storms for Improving ANS Predictor Performance** - This task would consider how new ANS predictors might be attained using knowledge of the physics of storms regardless of the current availability of data. Issues addressed in this task would be:

(a) Multi-tiered ANS layouts

(b) Relative value of currently unused types of physical measurements

(D) **Development of Processes for Routinely Evaluating Predictor Performance** - For the ranking trained ANS predictors this task would implement a range of evaluation processes in the User Interface. Issues addressed in this task would include:

(a) Accuracy or Skill levels

(b) Automatic testing

(E) **Investigation of Available Real-Time Processors for an ANS Lightning Predictor** - This task would survey real-time hardware (e.g. transputer boards) that could support a viable capability at a remote site. Issues addressed in this task will include[1]:

(a) Accelerated workstations (e.g. Macintosh™ IIx with transputer boards)

(b) Industrial process control machines (e.g. PIM™)

(F) **Develop LightningLynx© User Interface in Conjunction with KSC and Meteorologists** - The task would extend and test the User Interface functionality. This task would address a variety of candidates:

(a) Help menus,

(b) variation of user imposed sensor thresholds,

(c) 'strip chart' display of recent sensor data

(d) implement visible/audible alarm when prediction threshold is exceeded.

(e) Alternative ANS types

(G) **Cost/Benefit Ratios vs. Decision Thresholds at KSC** - This task would construct complete ROC graphs by varying decision thresholds. This task will investigate several issues:

(a) Alternative means for setting the most useful thresholds

(b) Alternative ways of presenting cost/benefits to KSC decision makers

(c) Effects of meteorology on optimal thresholds (i.e. weather regime, etc.)

The goal of the research and development program outlined above is the development of a robust, reliable lightning prediction system prototype which can be upgraded directly by meteorologists at remote sites using locally collected data.

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[1] PIM is a registered trademark of the Parallel Inference Machine of Flavors Technology of Amherst, NH

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